Characterization of MEG Patterns and Network Analysis during Meditation

Synopsis

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1. Introduction

Meditation is an ancient tradition practiced in many cultures around the world. Yet it is difficult to define, as it varies both between traditions and within them. In the scientific literature, meditation is defined as (1) self-regulation of the mind and body to bring mental processes under control, thereby promoting general well-being and developing specific skills (Walsh & Shapiro, 2006). (2) A practice in which individuals use a technique to train their awareness and attention to achieve a mentally clear and emotionally calm state (Cahn B & Polich John, 2006). However, according to Eastern philosophy, the primary goal of meditation is to attain "inner awakening", or similar experiential states as described in various contemplative traditions (Satsangi P S, 2013; Reddy & Roy, 2018). The philosophy is based on an aspect of hierarchical level of consciousness described in rudimentary model. According to the model, consciousness is intrinsic to the grand cosmos; both at macroscopic and microscopic levels. Man is perfect microcosm of the macrocosm. The Grand cosmos of macrocosm has three grand divisions universal spirit, universal mind, and the physical universe corresponds to white matter of the brain, grey matter of the brain and physical body. Any human being, by exploring outer world as science can only access physical universe. By taking recourse to meditation, it is possible for a living person to access other grand divisions resulting in inner awakening or inner experience (Satsangi P S, 2011; Satsangi P S, 2013).

During meditation, changes occur from one conscious state to other and are going to influence the brain. Neuroscientists study the influence of meditation by scanning the brain of Tibetans or nuns or meditationists of many schools of spiritual practices using modern neuroimaging techniques. Various modern neuroimaging techniques such as EEG (Stapleton P et al., 2020; Cahn B R & Polich J, 2006), MEG (Travis F et al., 2009; Berkovich-Ohana A et al., 2013), fMRI (Ives-Deliperi V L et al., 2013), fNIRS (Izzetoglu M et al., 2020) used to study about the influence of meditation. Further, to advance the scientific understanding of various meditation techniques, they have been classified on an empirical basis (Matko K & Sedlmeier P, 2019) and neural oscillation patterns (Kaur C and Singh P, 2015; Lee D Jet al., 2018). Classification on an empirical basis, based on the judgment of experienced meditators includes (1) focused attention and (2) open monitoring. Focused attention means concentrating on an object, attention to the breath, an idea, or a feeling, e.g., loving-kindness (Alba

B, 2013), repetition of a mantra, e.g., transcendental meditation (Roth R, 1987), and single-point meditation (Easwaran & Eknath,2018). Open observation involves focusing on consciousness itself includes mindfulness meditation (Kristeller J L, 2007), Zen, Isha Yoga, Shoonya Yoga, and Vipassana (Kasamatsu A & Hirai T 1966; Reddy & Roy, 2018). Meditation techniques classification based on neural oscillations, rhythmic patterns of neural activity in the central nervous system includes (1) focused attention, (2) open monitoring, (3) transcendental meditation, and (4) loving-kindness. These practices influence neural oscillations in specific brain regions (Kaur C and Singh P, 2015; Lee D J et al., 2018). Therefore, such studies can elucidate the relationship between these oscillation patterns and the benefits associated with these practices.

Since the early 1960s, many studies have been conducted to understand the effects of meditation (Cahn and Polich, 2006). The practice of meditation has many well-studied benefits, including improvements in cognitive function and overall well-being (Bxrentsen, 2015; Jones, 2019). Focused meditation has been shown to improve cognitive control abilities say enrich perceptual discrimination (Mac Lean et al., 2010), improve the handling of brain resources (Slagter et al., 2007), enhance attention (MacLean et al., 2010), improve inhibition of undesired responses (Sahdra et al., 2011), etc. Repeated practice of open monitoring meditation has been shown to improve the handling of brain resourcesduring memory function (Fujino M et al., 2018). Different meditation techniques mindfulness, Zen, transcendental, vihangam yoga, kirtan kirya, relaxation have been shown to improve cognitive functions in the context of aging and control of various neurodegenerative diseases (Marciniak R et al., 2014). Because of these improvements, meditation research has attracted significant interest in the cognitive neuroscience and medical communities.

In addition to the enhancements, these practices are associated with altered states of consciousness consistent with eastern philosophy. According to which, through meditational practice, one may transit beyond the levels in physical universe and gains consciousness about the higher levels in the macrocosm. This gain of consciousness affects the brain states which reflect the states of consciousness indirectly as neural correlates (Satsangi P S, 2015). Therefore, there exists one-to-one correspondence between inner experience and neural correlates. So, through study of meditation we can build an understanding about the macrocosmic universe. Thus, meditation studies are very

important.

Meditation practices are characterized by changes in brain rhythms such as theta, alpha, and gamma band activity in the anterior and posterior regions of the brain (Lee D J et al., 2018). The electrophysiological recordings of nuns showed an increase in theta and gamma-band power in the middle frontal and right parietal regions of the brain, respectively (Beauregard M & Paquette V, 2008). Several researchers have attempted to identify neural correlates associated with different meditational practices (Jerath R et al., 2012; Pagnoni G et al., 2008). In one such study with a group of Carmelitenuns, researchers used fMRI to identify and localize the neural correlates of a mystical experience when the nuns recalled the experience after the meditation session (Beauregard M & Paquette V, 2006). Different meditation practices lead to different patterns of brain activation and deactivation (Tomasino B et al., 2014). Moreover, the organization of the brain during meditation is understood by measuring connectivity patterns that form neural networks. In general, neural networks operate at multiple spatial and temporal scales, suggesting oscillatory synchronization as a key mechanism to explain information transmission (Cohen M X, 2014).

According to eastern philosophy, the correlates of consciousness can be measured in the form of dominant resonant frequencies (Satsangi P S, 2015). There is a scientific support available to support the philosophy. System and signals theory is in tune with sampling theorem and this theorem says that a higher frequency can observe the phenomenon of lower frequencies but not vice versa (Markan C M & Gupta P 2015). However, this states elsewhere by Swami Ved Bharati as subtler objects can observe the coarser objects but not vice versa (Bharati S V, 2006). Therefore, the crux of the model is to correlate various levels of consciousness with different levels of frequency at which a person resonates. Thus, a complete characterization of meditation can be made based on brain rhythms, brain activation patterns, and connectivity between the patterns obtained.

In characterizing meditation, several aspects are brought out. One of them is the activation patterns, categorized into two types (1) state effect – alteration in brain activities during the act of meditation, (2) trait effect – permanent changes due to long-term practice (Tang Y, 2017). Further, a comparison of activation patterns to psychological tasks or disorders could enhance the understanding. One of the review articles compared the meditation patterns with pain-related activity. The meditation practice

reduces pain due to its increased activity in ACC, insula, somatosensory cortex, and thalamus (Nakata H et al., 2014). Studies have shown that neural hypersynchrony is a cardinal feature of epilepsy and transcendental meditation (TM). So, TM practice may induce epilepsy or be antiepileptic therapy (Lansky E & Louis E, 2006). Therefore, the comparison of activation patterns helps to explore the anatomical aspect of the brain.

Apart from activation patterns, meditation is characterized in terms of brain rhythms. This measurement explores newer aspects about the nature of brain rhythms i.e., whether they are acting as anindividual oscillator or coupled oscillator. Thus, potentially allow for artificial manipulation in the treatment of disease (Lee D et al., 2018). In addition, the study of synchronization of brain rhythms during meditation helps to explore the mechanism of network formation in the brain. Networks are categorized into three types (1) random, (2) regular, and (3) small world. Small-world networks are of research interest as human brain networks follow small-world configuration (Liao X et al., 2017). A sudden comprehension that solves a problem is called insight ("Aha! moment") is characterized by the formation of small-world networks.

Therefore, the characterization of meditation in terms of brain rhythms, activation patterns, and connectivity patterns is of great importance. Previous studies have characterized meditation, but the results are not comparable because they vary. The wide variability in results is because (1) different meditation techniques have been evaluated and (2) relatively different sophisticated methods have been used to measure brain activation. To overcome the current situation of mixed and contradictory resultsan operational view to understanding meditation is now needed (Bærentsen K B, 2015). None of the previous work focused on formalizing the theory of meditation. Instead, there is a need for an empirical theory or a model that can form a basis for future research and applications. Thus, reduce variability in the results.

Therefore, this research aims to characterize meditation based on a rudimentary model. The model describes the aspects of hierarchical levels of consciousness (Satsangi, 2011; 2013). The transition to various levels of consciousness is possible by meditation practice i.e., "Surat-Shabd-Yog" as prescribed by the religion of saints. It is a systematic methodology for unifying the spirit force of a human being with the characteristic sound or frequency, which emanate from various levels of

consciousness (Satsangi, 2011; 2013).

2 Literature Review

In this chapter, a brief introduction to neuroimaging techniques, analysis methods include pre-processing, time series analysis, source localization, and connectivity analysis. Each section also provides the advantages and limitations of each technique.

2.1 Methods of neuroimaging studies

Neuroimaging uses either direct or indirect methods to measure the structural, functional, or pharmacological aspects of the brain. Neuroimaging can be divided into two types: (1) structural imaging, (2) functional imaging. Structural imaging measures the volume of different brain regions in anatomical view. This measure is used for the diagnosis of intracranial diseases and injuries. On the other hand, functional imaging provides visualization of how information is being processed during a particular task. Functional imaging measures the functions of the brain. This measure is used for the diagnosis of metabolic diseases, cognitive psychology, and in developing brain-computer interfacedevices.

There are several modalities of functional neuroimaging, among which choice can be made based upon the experimental question. A brief introduction to various methods is given below:

2.1.1 Magnetoencephalography (MEG)

Magnetoencephalography (MEG) is a non-invasive functional brain imaging technique. It consists of tiny sensitive sensors known as magnetometers, such as superconducting quantum inference devices (SQUIDs). They measure the tiny magnetic field generated by electrical signals in the brain. These measures can be used to produce patterns of spontaneous or evoked brain activity. MEG is housed in a magnetically shielded room to attenuate the external magnetic noises. MEG measures neural assemblies with a high signal-to-noise ratio and temporal resolution. MEG fields pass through the head without any distortion. MEG provides high spatial resolution in comparison to EEG (Singh S P, 2014). MEGpreparation time of the experiment is less in comparison to EEG but its expensive equipment.

Modern Elekta Neuro MEG consists of 102 magnetometers and 204 planar gradiometers, a total of 306 sensors within a hemispherical array. Magnetometers measure the magnetic field perpendicular

to the surface. While the gradiometer measures the spatial gradient of the field rather than the magnitude. Magnetometer measures are sensitive for both nearby sources and distant sources, whereas planar gradiometers measure the sources exactly underneath the sensor. Magnetometers measure total flux (Tesla), while gradiometers measure a gradient (Tesla/meter). Thus, they suffer from different levels of noise. Therefore, estimation of source activity requires some scaling that determines the relative contribution of each modality. This scaling depends on the SNR (signal-to-noise-ratio) measurement of each modality, this is estimated by noise measurement i.e., empty room data (Mohseni H R et al., 2012).

2.1.2 Electroencephalography (EEG)

Electroencephalography (EEG) monitors electrical activity at the scalp of the brain. It measures the difference between the potential at the sensor and a reference point (generally GND), units of measurement – microvolts (μV). EEG provides high temporal resolution, by measuring the neural assemblies on the order of milliseconds. On the other hand, the spatial resolution provided by EEG is limited; due to a smaller number of electrodes, low-signal-to-noise ratio (Bell M A & Cuevas K, 2012). EEG is less expensive with high preparation time but the ongoing research on having semi-dry electrodes will compensate for this issue (Li, G et al., 2020). EEG is generally used in cognitive measurements or to diagnose conditions such as epilepsy and sleep disorders.

2.1.3 functional magnetic resonance imaging (fMRI)

The changes with time in paramagnetic properties of oxy and deoxygenated hemoglobin are measured using fMRI to create images of change in the blood. These changes are associated with the neural activity during a cognitive state or resting state of the brain (Glover G H, 2011). The spatial resolution of fMRI is high, it is around two-three millimeters. However, temporal resolution is limited due to hemodynamic response, nearly two-five seconds. fMRI measurements have high signal-to-noise- ratio due to which they have been widely employed in thousands of clinical studies such as surgical, monitoring treatment disorders, etc. Further, a baseline state is required in experiment design, so that neural activity during the target state is measure by subtracting from the baseline state (Crosson B Fordet al., 2010).

2.1.4 Functional Near-infrared Spectroscopy (fNIRS)

Functional Near-infrared Spectroscopy (fNIRS) is used for visualizing brain tissue function. Infrared (650-900 nm) can penetrate through the skull, typically a centimeter or two in adult brain. NIRS measures the changes in the concentration of oxygenated and deoxygenated hemoglobin in the blood. The spatial resolution of NIRS is slightly less than a cm, temporal resolution is around one-ten milliseconds (ms). However, the temporal resolution is better than fMRI. NIRS is relatively low cost compared to MR andis portable, can be used in a normal and unconfined environment. It is used in clinical settings for the detection of superficial brain regions (Crosson B Ford et al., 2010).

Further, multi-modal imaging is the concept of bringing together observations or measurements from different instruments. Multi-modal studies are important as they eliminate any possible machine or technique-related artifacts. In this regard, many such techniques are often used both singularly and in conjunction, say (i) Magnetoencephalography (MEG), (ii) Electroencephalography (EEG), (iii) Functional magnetic resonance imaging (fMRI), (iv) Functional Near-infrared spectroscopy (fNIRS).

Table 1: Comparison of different types of Neuroimaging Techniques

Methods	MEG	EEG	fMRI	fNIRS
Measures	Measures electric dipole activity (tangentially oriented) (Singh S P, 2014).	Measures electric dipole activity (radially oriented) (Bell M A & Cuevas K, 2012).	Measures blood oxygenation, blood flow, & Blood volume commonly called Blood oxygenation level dependent (BOLD) (Glover G H, 2011).	Measures changes in oxygenated and deoxygenated haemoglobin (Quaresima V & Ferrari M, 2019).
Type of sensors/Channels	measured by using SQUIDS (Superconducting interference devices) (Singh S P, 2014).	Brain activity is measured by using electrodes (Bell M A & Cuevas K, 2012).	Brain activity is measured by using Nuclear Magnetic Resonance coupled with gradients in the magnetic fields to create images. (Glover G H, 2011).	Brain activity is measured by using near-infrared light to estimate cortical hemodynamic activity (Quaresima V & Ferrari M, 2019).
Temperature	Measurements are carried out by SQUIDS, generally placed inside liquid helium at -296^{o}C (Velmurugan, J et al., 2014)	Measurements are carried out at room temperatures (Light, G. A et al., 2010)	Measurements are carried out at room temperatures (Involving R I M E, 2007).	Measurements are carried out at room temperatures (Tsow, F, et al., 2021)

Temporal Resolution	milliseconds (ms) (Babiloni, F et al., 2004)	milliseconds (ms) (Babiloni, F et al., 2004)	5 to 6 s (Glover G H, 2011).	0.1 s to 1s (Quaresima V & Ferrari M, 2019).
Sampling Rates	290 Hz to 1200 Hz (Velmurugan, J et al., 2014)	256 Hz to 1024 Hz (Chen, W. L et al., 2020)	2 Hz to 3 Hz. Typical TR (Repetition time) > 0.4 s in most of the fMRI's (Huotari, N et al., 2019)	25 to 100 Hz (Quaresima V & Ferrari M, 2019).
Detection of brain rhythms	145 Hz to 600 Hz (according to Nyquist theorem; Markan & Gupta, 2015)	128 Hz to 512 Hz (according to Nyquist theorem; Markan & Gupta, 2015).	Less than 1 Hz (Glover G H, 2011).	Typically ranges between 1 to 10 Hz as it detects hemodynamic signals (Quaresima V & Ferrari M, 2019).
Spatial Resolution	Offers moderate spatial resolution of around 1 cm (Smits K, 2020)	Offers poor spatial resolution of around 5-9 cm (Burle, B et al., 2015).	Offers high spatial resolution of around 3–4 mm (Glover G H, 2011).	Offers moderate spatial resolution of around 1 cm (Quaresima V & Ferrari M, 2019).
Number of sensors/Channels	The number of sensors varies from 16 (Kim Y J et al., 2019) to 306 sensors (102 magnetometers and 204 planar gradiometers) (Mohseni H R et al., 2012).	The number of channels varies from 32 to 256. (Montoya-Martínez, J et al., 2021)	In MRI the MR signal is produced based on the resonance phenomenon produced by radiofrequency (RF) pulses. RF coils of MRI are of two types (1) volume coils, and (2) surface coils. Most clinical MRI scanners include volume coils to perform whole-body imaging and smaller volume coils for the head. The large field of volume coils receives noise from the whole body, not just a region of interest. Whereas surface coils are designed to provide high RF sensitivity over a small region of interest (ROI), act as ideal receivers, as they only detect from ROI. The number of surface coils generally varies between 32 to 64 (Keil, B et al., 2013).	The number of channels varies from 16 to 47 (Llana, T et al., 2022)

Comfort Of meditator	highly comfortable with MEG as it is placed away from head and takes less preparation time.	Less comfortable as it placed on the scalp and as it takes longer preparation time	Less comfortable as it produces lots of noise and requires lying down position which is not suitable for meditation practice.	Moderately comfortable as it is placed on the scalp, but the preparation time is less.

One chooses a technique that can most accurately answer the experimental question. Since the hypothesis being examined in this thesis is based on the Power Law of Meditational Consciousness (PLMC) (Satsangi P S, 2015) hence the objective is to explore the neural frequency correlates and identify characteristic signatures at every meditational stage of the brain. Therefore, a technique with a high temporal and spatial resolution is important for this study. So, we have chosen MEG.

The objective of the study is to explore the neural frequency correlates to identify characteristic signatures at every meditational stage of the brain. In this regard, EEG/MEG are better suited to record and analyze high-frequency activity compared to fMRI/fNIRS. In detail fMRI & fNIRS have sampling rates ranging from 2 to 3 Hz & 25 to 100 Hz, so the frequency of activities that have been measured ranges from 1 to 1.5 Hz & 12.5 to 50 Hz respectively, according to the Nyquist theorem (Markan & Gupta, 2015). Even though the sampling frequency of fNIRS is high, it measures hemodynamic signals which oscillate at 2 Hz. So, practically fNIRS accurately measures the brain activities up to 10 Hz (Quaresima V & Ferrari M, 2019). Therefore, the measurements by fMRI/fNIRS are limited, ignoring higher-order contributions (high-frequency activities) & not suitable for the present study.

In the case of EEG/MEG, MEG is supposed to be superior as (1) the MEG field passes through the head without any distortion, (2) MEG unlike EEG placed away from the scalp & therefore won't disturb the meditator and (3) MEG provides high spatial resolution compared to EEG (Singh S P, 2014). However, regarding source localization fMRI is the only technique that directly records deep brain activity. All other techniques such as EEG/MEG and fNIRS are sensor techniques and they use a computational method to infer deep-brain activity or source localizations, using fNIRS cortical activities are generally measured. Thus, fMRI does appear to be a suitable cross-modality study that can help substantiate the inferred localization results, especially in deep brain regions. However, we are skeptical about using fMRI because (1) Some meditators may have a claustrophobic feeling inside the fMRI chamber, (2)

fMRI environments are noisy and may disturb the meditators' attention, and (3) fMRI requires a lying down position which may not be a suitable position for meditation (Glover G H, 2011). Therefore, technically fMRI is a suitable cross-modality, but the meditation phenomenon under measurement is sensitive and has some physical limitations mentioned above.

Among EEG/MEG & fNIRS, MEG offers reasonable source localization as these computational methods of localization are dependent on the number of channels (Singh S P, 2014) & MEG consists of 306 channels, the highest number of channels than that of any other techniques. Still, the most multi-modal studies include co-registration of high spatial and temporal offering techniques, say EEG and fMRI. In One such study on Carmelite nuns conducted using EEG and fMRI during recall of mystical experiences, the source localizations measured through EEG are corroborated with fMRI measurements (Beauregard M & Paquette V, 2006; Beauregard M & Paquette V, 2008). Therefore, fMRI measurements can be used to validate the results of source localization by other modalities.

On the other hand, MEG and fMRI are complementary modalities, as MEG uses sensitive superconducting quantum interference devices (SQUIDs) that cannot be combined with conventional high-field MRI in a single instrument (Zotev, V. S et al., 2008). In the given time and space, we will try to collect EEG & fMRI data. So that MEG data can be compared with EEG data & fMRI source localization data can be used for validating MEG localization results. Therefore, it's clear that none of the techniques EEG or fMRI data can add new results to the present study. Overall, MEG provides the primary results, and the other modalities provide confirmatory results that can be corroborated with the primary results. If not, possible to collect secondary data we will try to rely on existing literature and compare the MEG data results with the pre-existing multi-modal studies data.

2.2. Analysis methods

This subsection will briefly review some of the commonly used methods of analysis in functional imaging.

2.2.1 Preprocessing

Data that captures the transient nature of brain activity is required to understand the brain dynamics during meditation. The high-resolution MEG measurements, collected during meditation in this research,provide such data. Preprocessing is the first crucial step of the analysis. It prepares the data

so that other analyses can be performed on it. The data preprocessing involves artifact correction and filtering.

Artifact correction

The data should be clean for any analysis to be successful i.e., it should originate purely from the neural sources. The most common types of artifacts that drive from subjects include muscular artifacts, blinks, and heartbeats. Further, sensors can also be affected by non-biological artifacts, interference of power lines (electrical appliances operate at 50Hz in India). The correction can be done by identifying topographies corresponding to artifacts (i.e., the spatial distributions at a one-time point) and remove them from recordings. This spatial decomposition can be done using either SSP (signal-space-projection)or ICA (Independent component analysis) methods. SSP has been mostly used in MEG studies, while ICA in EEG studies (Haumann N T et al., 2016).

Filtering

The artifact due to electronic noise is removed by applying a notch filter at 50 Hz, 100 Hz, and 150 Hz (in harmonics). Further, several oscillations have been found in the human brain, ranging from slow oscillations (0.5 Hz) to very high frequencies (600 Hz). To measure brain rhythms, they were classified into various frequency bands. There are broadly two main reasons for this classification (1) Power-law distribution (1/f); power is inversely proportional to frequency (Satsangi P S et al., 2015; Srivastava D P et al., 2017). (2) Wiring of the brain and neuronal communication between the neurons. Due to power law high frequencies are not observed along with low frequencies. The neuronal communication is done at various levels, for long-distance communication slow-moving signals are preferred and for small distance communication high-frequency signals are preferred. The wiring of the brain optimizes the use of both slow and fast frequencies. The classification of frequency bands includes delta 0.5-4 Hz, theta 4- 8 Hz, alpha 8-13 Hz, beta 13-30 Hz, gamma 30-80 Hz, fast 80-200 Hz, ultrafast 200-600 Hz (Buzsaki G, 2006). Further, these bands can be divided into smaller bands say gamma1 30-45, gamma 2 45-60 Hz, etc. depending on the experimental question.

2.2.2 Time-series analysis

A time series consists of a series of data points. They are analyzed to make predictions or to understand the underlying dynamics of the series. Time-series analysis methods have been used

widely in many domains, ranging from econometrics, weather forecast, earthquake prediction, astronomy, brain data, and largely in any domain of applied science and engineering. This subsection will briefly review some of the commonly used methods in functional brain imaging.

Spectral analysis

The oscillatory activity in any time series can be naturally represented as a superposition of several oscillation components (Matsuda T & Komaki F, 2017). Thus, spectral analysis is computed to estimate the contributions of various frequencies on the measured MEG data. Spectral analysis is broadly classified into two areas (1) Fourier transforms, (2) PSD (power spectral density). FFT (Fast Fourier Transform) is the most common approach used for spectral analysis. FFT converts a time-varying signal into a frequency spectrum. Fourier theorem states that any time series can be represented as a linear combination of sines and cosines with varying weights. The FFT spectrum samples the input signal to compute the magnitude of sine and cosine components in it and displays the spectrum of these measured frequency components (Analyzers D.C.F; https://www.thinksrs.com/downloads/pdfs/applicationnotes/AboutFFTs.pdf). PSD is performed using the Welch method, based on FFT, which makes it computationally efficient. Fourier transform is preferred when data is noise-free and deterministic, while on other hand PSD is preferred when data contains random effects or noise. Welch method averages the data over short overlapping windows and smoothens the data to see desired phenomenon (Solomon O M, 1991).

Time-frequency analysis

Spectral analysis is important for many reasons, but it does not provide information on temporal changes in frequency. MEG is a dynamic phenomenon, and it is, therefore, necessary to investigate its transient nature over time. The commonly used methods for obtaining time-frequency representations are (1) Complex Morlet wavelets decomposition, (2) multi-tapers. A sine wave windowed with a Gaussian iscalled a Morlet, this is a way to localize dynamic patterns of frequency structure in a time series. Complex Morlet is used for the estimation of power and phase of time-varying frequency bands. Thus, a Complex wavelet occupies a 3D space: time, real (power), and imaginary (phase). Few parameters are to be taken care of during the computation of Complex wavelets (1) minimum number of frequencies of thewavelets, (2) a maximum number of frequencies

of the wavelets, (3) number of wavelet cycles used for Gaussian taper. The minimum and the maximum number of frequencies depend on the task design and hypothesis. Especially for high frequency, the sampling rate should be high i.e., they cannot be higher than Nyquist frequency (if the sampling frequency is 1000 Hz, the maximum frequency that can be analyzed is 500Hz). The number of wavelet cycles of the Gaussian taper defines the width of thewavelet. This parameter controls the trade-off between temporal and frequency precisions. Many cycles give better frequency precision with low temporal precision and vice versa. This number depends on the goal of the analysis. For observing transient changes in inactivity, a small number of cycles (three orfour) are preferred. For a relatively long trial period, many cycles (seven or ten) are preferred. If temporal and spatial precision is important for a study, then one can perform the analysis twice (Cohen M X, 2014). The multi-taper method is used for tapering the edge artifacts, contaminate the frequency representation. It is particularly useful for situations of (1) low signal-to-noise ratio, (2) single-trial analysis, (3) focus on high-frequency power, above 60 Hz. The multi-taper approach increases the smoothens the power of high frequencies, by applying tapers, which facilitates cross-subject averaging. The smoothing is done by extracting a time segment, the data from the time segment are multiplied by a series of tapers, FFT of each tapered time series is computed and averaged. This method is not preferred for analyzing low frequencies, particularly around 30 Hz (Cohen M X, 2014).

Topographical analysis

MEG mapping, or topographical analysis, considers the value at each sensor and through interpolation, displays the field distribution of brain electric activity over the whole scalp (2D projections). It provides a global picture of activation at the scalp by considering all sensors at once. However, it does not provide any additional information about sources underlying the scalp (Cohen MX, 2014). Nonetheless, it is useful method to visualize the results.

2.2.3 Source Localization

Source localization is a method to determine the location of the activity within the brain by using sensor measures. This is termed an inverse problem. The inverse problem is ill-posed, as the problem does not have a unique solution i.e., there can be infinitely many sources activity pattern that corresponds to same sensor topography. Thus, the solution of the problem is determined using either

an overdetermined model or an underdetermined model. The underdetermined models are associated with a risk of a decrease in the robustness of results and an increase in errors, so in general overdetermined models with specific refinements are preferred. The popular M/EEG source estimation methods are L2- minimum-norm-estimation (MNE); dynamical statistical parametric mapping (dSPM), standardized or low-resolution electromagnetic tomography (s/eLORETA), and linearly constrained beamformers. L2- MNE, dSPM, and s/eLORETA are linear source estimation methods based on overdetermined models (Hauk, O et al., 2019).Localization algorithm using overdetermined models initializes with a guess followed by a loop. In the loop, the forward model is used to estimate the magnetic field from the guess and then adjusted to reduce the difference between the estimated and the measured fields. In contrast, there exists another approach where the ill-posed inverse problem is ignored and estimates the current at a fixed location.This approach uses beamforming techniques. The evaluation of source estimation depends on the measurement configuration (number of magnetometers, gradiometers, and electrodes), head model (spherically symmetric, realistic single shell, three-shell) as well as the SNR (signal-to-noise-ratio) and noise covariance of the data (Hauk, O et al., 2019).

Localization algorithm as described by Olf Hauk (Hauk, O et al., 2019) is as follows

Let the measured data by n channels **d** (nx1), the source distribution **s** (vector mx1) then the relation between **s** and **d** in matrix form.

$$\mathbf{d} = \mathrm{L}\mathbf{s} + \mathbf{e}$$

Where **L** is called lead field matrix, contains information about the head shape, measurement configurations (sensors), and the physics of signal generation (quasi-static approximation of Maxwell's equation) and $\boldsymbol{e}$ is an error term.

Source estimation using optimal linear matrix G.

$$\hat{\mathbf{s}} = \mathbf{G}\mathbf{d} = \mathbf{G}(\mathbf{L}\mathbf{s} + \mathbf{e}) = \mathbf{R}\mathbf{s} + \mathbf{G}\mathbf{e}$$

Where **R** is the resolution matrix that provides desired relation between true and estimated sources.

Noise and regularization

In source estimation noise suppression is necessary, to remove signals from outside the brain i.e., to minimize noise term **Ge**. The regularization parameter **λ** (lambda), controls the degree of regularization.

In general, SNR is set to 3 for getting good source estimation and the minimum value is 0.1.

L2-MNE

An expression for the weighted L2-MNE is

$$\mathbf{G_{MNE}} = \mathbf{L^T}\left(\mathbf{LL^T} + \boldsymbol{\lambda}\mathbf{C}\right)^{-\mathbf{1}}$$

Where **C** is the noise covariance matrix. The resolution matrix in this case is.

$$\mathbf{R_{MNE}} = \mathbf{L^T}\left(\mathbf{LL^T} + \boldsymbol{\lambda}\mathbf{C}\right)^{-\mathbf{1}}\mathbf{L}$$

To boost the impact of deep sources $\mathbf{G_{MNE}}$ is multiplied by a diagonal weighting matrix **W**.

$$\mathbf{G_W} = \mathbf{W}\mathbf{G_{MNE}}$$

The resolution matrix accordingly

$$\mathbf{R_{nMNE}} = \mathbf{W}\mathbf{R_{MNE}}$$

dSPM & sLORETA

The normalization matrix of dSPM contains the minimum norm estimates of noise at each source, derived from the noise covariance matrix.

$$\mathbf{W_{dSPM}} = \sqrt{\mathbf{Diag}\left(\mathbf{G_{MNE}}\mathbf{C}\mathbf{G_{MNE}^T}\right)}^{-\mathbf{1}}$$

sLORETA uses the diagonal of the MNE resolution matrix for normalization.

$$\mathbf{W_{sLOR}} = \sqrt{\mathbf{Diag}(\mathbf{R_{MNE}})}^{-\mathbf{1}} = \sqrt{\mathbf{Diag}(\mathbf{L^T}(\mathbf{LL^T} + \boldsymbol{\lambda}\mathbf{C})^{-\mathbf{1}}\mathbf{L})}^{-\mathbf{1}}$$

The MNE solutions have a strong source bias as they estimate source density (units A-m) which isnot normalized by area. dSPM and sLORETA are normalization measures of MNE (unitless). These approaches produce zero localization errors especially in the absence of a noisy environment. The reported localization error of dSPM and sLORETA in noisy environments is approximately on the order of 1-2cm (Pascual-Marqui R D, 2002; Samuelsson J G et al., 2021).

Beamformer takes an adaptive spatial-filtering approach, each location is considered as a predefined region of interest (ROI) in source space while suppressing the contributions from other locations. There are two broad classifications of beamformers (1) vector beamformer consider all source orientations, (2) scalar beamformer considers predefined source orientation. Scalar beamformers have a high spatial resolution in comparison to vector beamformers (Jaiswal A et al., 2020).

Beamforming algorithm as described by Jaiswal (Jaiswal A et al., 2020) is as follows

Let x (Mx1) be measured data from M sensors, N be number of grid points in the ROI $\mathbf{r_j}$, (j=1, …, N). The source $\mathbf{y(r_j)}$ at any location $\mathbf{r_j}$ is estimated as a weighted combination of the measurement x as

$$\mathbf{y(r_j)} = \mathbf{W^T(r_j)x}$$

Where $\mathbf{W(r_j)}$ is known as a spatial filter for a source at a location $\mathbf{r_j}$. The spatial filter $\mathbf{W(r_j)}$ for vector beamformer is defined as

$$\mathbf{W^T(r_j)} = \mathbf{[L^T(r_j)C^{-1}L(r_j)]^{-1}}$$

Where $\mathbf{L(r_j)}$is the local lead field matrix & C is the covariance matrix.

The output variance of source power is estimated at each point in source space and normalized with projected noise $\mathbf{C_n}$ variance over the baseline variance for computation of source localization. This estimate is called Neural Activity Index (NAI) and is expressed as

$$\mathbf{NAI(r_j)} = \mathbf{Trace}\left\{\mathbf{[L^T(r_j)C^{-1}L(r_j)]^{-1}}\right\}\mathbf{/Trace}\left\{\mathbf{[L^T(r_j){C_n}^{-1}L(r_j)]^{-1}}\right\}$$

Scanning over all locations as ROI transforms the MEG data into an NAI map. One of the disadvantages of linear methods is high spatial dispersion even when SNR is infinity. So, to overcome this disadvantage MxNE (mixed norm imaging), a non-linear method is explored. A study has shown that MxNE offers low spatial dispersion and low localization error as small as sLORETA. Low spatial dispersion is interesting as it provides the ability to distinguish multiple sources (Samuelsson J G et al., 2021).

2.3 Connectivity analysis

Before the1980s, neurons were thought to collect information through action potential, when excited by sensory input. Later, the collective behavior of many neurons was studied. These studies have provided insights into large-scale operations of the brain as connected networks (Buzsaki G, 2006). The brain networks are complex; operate at multiple spatial and temporal scales using synchronization as a key mechanism for information transmission (Cohen M X, 2014). Network connectivity analyses study the communication network maps of the brain both in source and sensor space. Brain connectivity is of three types (1) structural connectivity, (2) functional connectivity, and (3) effective connectivity.

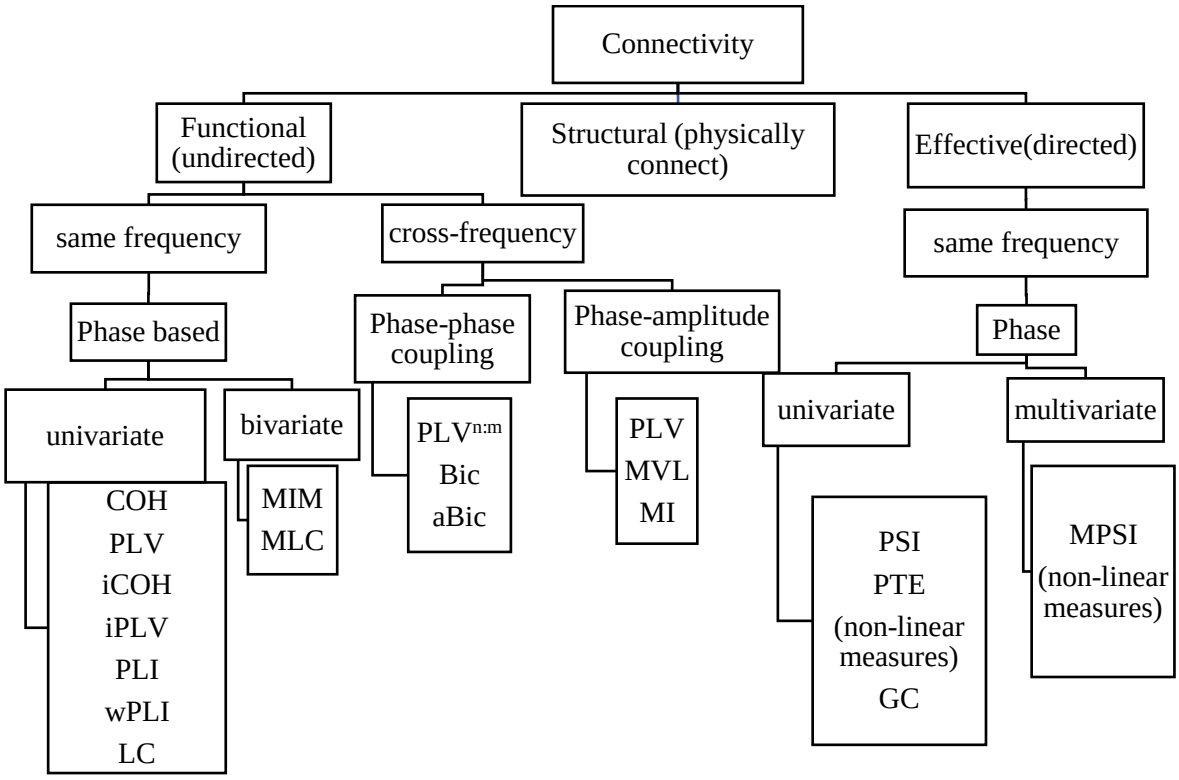

Figure 1: Broad classification of brain connectivity measures

The classificationsare based on the interaction type (same frequency, cross frequency), directionality, univariate, or multivariate connectivity measures. Structural connectivity is an anatomical network map based on the detection of fiber tracts that are physically connected. Functional connectivity identifies brain regions that are connected to perform specific tasks or brain functions. The connectivity between regions is identified based on a similar frequency, phase, and or amplitude. Effective connectivity determines the direction of information flow between the brain regions, identified in the functional connectivity (Bowyer S M, 2016). Brain connectivity can be assessed based on different measures as shown in the table. This subsection will briefly review some of these methods.

3 Motivation

There is an overwhelming modern scientific opinion that considers all aspects of the human mind and consciousness as an outcome of physical processes occurring in brains. However, there is an alternate opinion (Kelly et al., 2007) that does not limit consciousness as merely an epiphenomenon of brain activity. Such views echo the ancient Indian philosophy that experientially subscribes to a

slant of reality that postulates hierarchical levels of consciousness (Awasthi B, 2013). The aspect of hierarchical levels of consciousness has comprehensively formulated in a rudimentary framework by Revered Prof. P. S. Satsangi. The framework is about the creational system that spans across not only the physical processes but also esoteric processes relating to the body, mind, and spirit (Satsangi, 2011; 2013). According to this framework, the human body, blessed with specific latent faculties. By awakening thesefaculties, one is revealed or made privy to the secrets of the macrocosm associated with mystical experiences. The process of awakening these faculties involves turning inwards and concentrating on specific ganglia in the physical body or nerve centers in the brain present in the human microcosm. In this sense, these nerve centers (or referential centers) are considered apertures or means of communication to access macrocosm through a microcosm. The art of meditation, as explained in Surat- Shabda-Yoga, is the systematic methodology to achieve resonance by harmonizing with rhythms of internal sounds or vibration frequencies produced at different referential centers (neural correlates) that correspond to states of consciousness or different levels of reality (subtlety) so that at each level inherent functions manifest themselves in a highly increasing progression.

Such views bring forth the mind-brain relationship without ignoring the possibility of non-brain-based consciousness. However, these are experiential descriptions often disregarded due to a lack of experimental evidence in support. Progress in this direction is bound to examine these hypotheses empirically to have a reasonable justification for any a priori restrictions to the nature of consciousness. On the other hand, some of the conjectures can withstand rigorous scientific inspection, it can enormously impact the current understanding (Sedlmeier P& Srinivas K, 2016). In this regard, two novel MEG studies, which have recently been designed at DEI Center for Consciousness Studies to record experiential neural correlates. The first study uses an indigenous MEG (16 probes) for data collection, for the first time a set of frequencies that include 3, 4.5, 76, 108, and 126Hz that characterize the groupof meditation practitioners at Dayalbagh (Satsangi P S, 2015). The second study extends it further by pioneering a methodology that associates experimentally measured meditation state frequencies with first-person experiential reports from transcendental meditation practitioners post their meditation session. These two experiments together

demonstrate the hierarchical nature of first-person meditational experiences through their frequency-specific neural correlates and established the Power law of meditational consciousness (Satsangi P S, 2015).

While these novel experiments scientifically associate vibration or frequency with states of consciousness, they also provide credibility to the proposition that lower frequencies correspond to the grosser mind (lower mind) and higher frequencies correspond to subtler mind (higher mind), thereby attempting to measuring the immeasurable (Bharati S V, 2011). The invoking sampling theorem (Nyquist criterion) highlights an observational hierarchy inherent in neural frequency correlates associated with conscious states where subtler (higher frequency) can observe or reconstruct the grosser (lower frequency) but not vice versa (Markan & Gupta, 2015). Reiterates the same fact from the quote of Upanishads of ancient Indian philosophy "मनसामनआलोक्यतत्त्यजेत्परमंपदम्। (manasāmanaālokyatattyajetparamaṃpadam) [https://upanishads.org.in/otherupanishads/63/3/5] - the principle of self-observation, and its practice guided by experts, is to bemaintained as one progress into higher and yet higher states of meditation. Here subtler mind observesthe grosser mind, which assesses its progress, and answers the question as to "where am I in mymeditation?" (Bharati S V, 2006).

The basis of research work is on a rudimentary model and its formulation in lab settings. This study is inspired by power law of meditational consciousness and its relationship with first person inner experience. The aim of this research is to identify and understand the nature of frequency correlates (Satsangi P S et al., 2015). This is done by measuring oscillatory patterns and connectivity patterns during meditation. Such insight would be useful in formulating the characterization of meditation in lab settings and be applied to real-world settings. Therefore, through a close interaction between the rudimentary modeling framework and the experiment, this study will formalize the descriptions that characterize meditation and the testable predictions.

The goal of this research is to analyze and understand the neuronal dynamics of meditation. High temporal and reasonable spatial resolutions are required to analyze oscillatory dynamics and localize the source the source activity. Both MEG and high-density EEG offer high temporal and spatial

resolution. Especially in the study of meditation the data collection setup should not disturb the meditator. So, MEG is preferable over EEG as MEG does not touch the scalp, it's placed away from it but for EEG the cap is placed over the scalp.

The brain activity of the participants will be recorded using MEG for a session of ten minutes, while the meditators group practiced *"Surat-Shabd-Yog"* and compared it with the aspirants or control meditators (CM) group having no meditative experience practiced chakra meditation. The Meditating group consisted of Advanced meditators (AM) and Beginner meditators (BM). Preliminary data of the participant's was recorded using Elekta Neuro MEG TRIUX in March 2019 at Gurugram, India.

4 Proposed Plan of Study

The focus of the research will be to

Study the effect of meditation on the brain both as short term or instantaneous effect during a meditational session (state effect) and long-term effect observed over years of meditational experience (trait effect). The proposed objectives are

1. Study Changes in
    - Spectral power of recorded MEG data.
    - Identify 'hot spots' (source localizations by using state-of-the-art numerical methods like sLORETA) of frequency band-specific activity.
    - Perform group analysis for AM, BM and CM groups and compare.
2. Analyze Connectivity
    - Both frequency band specific and across bands.
    - Explore graph theoretical measures to study topological architecture of human brain networks, such as small-worldliness, modular organization, and highly connected or centralized hubs.
    - Perform group analysis for AM, BM and CM groups and compare.
3. Examine the role of frequency band 'hot spots' as 'brain apertures.'

The research thesis will be a suitable conglomerate of the above-defined areas.

5 Methodology

The brain activity of participants will be recorded at 1000 Hz sampling frequency along with

heartbeat and eye-blink using MEG. Psychometric data of the participants will be collected at the end of the meditation session, to assess the quality of the meditative state. We will use a 5-points scale to assess (1: very bad, 5: very good) on relaxation and (1: little hindrance, 5: highly disturbing) hindrance items extracted from the meditation depth questionnaire, a validated questionnaire to assess the depth dimension of meditation (Piron H, 2001).

MEG data is extremely rich and multifaceted. Several packages have been developed for analyzing MEG data. Most popular software packages include Brainstorm; Field Trip; MNE-Python; EEGLABand SPM. These are all available under public domain license, can be shared and modified by anyone. Commercial software packages under proprietary license include BESA and CURRY (Andersen L M, 2019). We will use Brainstorm (Tadel et al., 2011), BESA (Brain Electrical Source Analysis; www.besa.de; BESA GmbH) and MATLAB for data analysis. Preliminary data was collected in March 2019.

Analysis of the data includes artifact correction using Signal-Space Projection (SSP). The data was band-pass filtered into five frequency bands delta: 0.5-4 Hz, theta: 4-8 Hz, alpha: 8-13 Hz, beta: 13-30 Hz, gamma1: 30-45 Hz. In each frequency band, corrected raw data will be divided into ten epochs (1 epoch for each minute of a meditation session). Out of these ten epochs, three epochs corresponding to the start means 1-2 min at the beginning, mid means 5-6 min in between the session, and end means 9-10 min at the end of the session was be analyzed further. To perform source localization sLORETA method will be opted as it is a normalized method and have high localization accuracy (Pascual-Marqui R D, 2002; Samuelsson J G et al., 2021). *State effects* are straightforward as they require measurement to be done over a short period of time. We do it here by comparing the start, mid, and end epochs of the ten-minute meditation session.

The *Trait effects* on the other hand are challenging as they require effects to be measured on a subject over decades which may not be feasible in a PhD thesis (given the limited time scale). However, most researchers attempt to get an estimate of the same by comparing human subjects at different stages of their meditational journey (Braboszcz C et al., 2017.) For example, here we have three categories of meditators representing different stages i.e., CM (starting stage, up to 21 years), BM (nascent stage, up to 40 years) and AM (advanced stage, beyond 40 years). The stages are however not associated to

age but to the inner experiences. Here we are assuming that the human brain is anatomically very similar and based on experiences it adapts to acquire a distinct character. As far as meditational effort and experiences are concerned, its related neural frequency correlates exhibit a characteristic signature at every meditational stage of the brain. Thus, even though trait effects are not being measured in the strict meaning of the word they are however being estimated by comparing various meditational stages. This is based on experiential observations over large masses over hundreds of years as documented by those adepts at these meditational practices.

Preliminary study on Neural correlates during meditation verifies a frequency hierarchy was presented in the form of an Oral Presentation in the 20th Conference on Dayalbagh Science of Consciousness (DSC) held at Dayalbagh Educational Institute, Agra between 23 May 2020.

6 References

Alba, B. (2013). Loving-kindness meditation: A field study. Contemporary Buddhism, 14(2), 187-203.

Andersen, L. M. (2019). Software and resources for experiments and data analysis of MEG and EEG data (No. e27988v2). PeerJ Preprints.

Analyzers, D. C. F. About FFT Spectrum Analyzers. (https://www.thinksrs.com/downloads/pdfs/applicationnotes/AboutFFTs.pdf)

Awasthi B. (2013). Issues and perspectives in meditation research: in search for a definition. Frontiers in psychology, 3, 613.

Bartz, S., Andreou, C., & Nolte, G. (2020). Beyond pairwise interactions: the totally antisymmetric part of the bispectrum as coupling measure of at least three interacting sources. Frontiers in Neuroinformatics, 14, 48.

Basti, A., Nili, H., Hauk, O., Marzetti, L., & Henson, R. N. (2020). Multi-dimensional connectivity: a conceptual and mathematical review. NeuroImage, 117179.

Bastos, A. M., & Schoffelen, J. M. (2016). A tutorial review of functional connectivity analysis methods and their interpretational pitfalls. Frontiers in systems neuroscience, 9, 175.

Beauregard, M., & Paquette, V. (2006). Neural correlates of a mystical experience in Carmelite nuns. Neuroscience letters, 405(3), 186-190.

Beauregard, M., & Paquette, V. (2008). EEG activity in Carmelite nuns during a mystical experience. Neuroscience letters, 444(1), 1-4.

Babiloni, F., Mattia, D., Babiloni, C., Astolfi, L., Salinari, S., Basilisco, A., ... & Cincotti, F. (2004). Multimodal integration of EEG, MEG and fMRI data for the solution of the neuroimage puzzle. Magnetic resonance imaging, 22(10), 1471-1476.

Berkovich-Ohana, A., Dor-Ziderman, Y., Glicksohn, J., & Goldstein, A. (2013). Alterations in the sense of time, space, and body in the mindfulness-trained brain: a neurophenomenologically-guided MEG study. Frontiers in psychology, 4, 912.

Bell, M. A., & Cuevas, K. (2012). Using EEG to study cognitive development: Issues and practices. Journal of cognition and development, 13(3), 281-294.

BESA GmbH, Freihamer Str. 18, 82166 Graefelfing, Germany (www.besa.de).

Bharati, Swami Ved (2011) Consciousness: Measurable or Immeasurable? Spirituality and Science of Consciousness, Ramakrishna Mission Institute of Culture, Kolkata, pp. 116-141, ISBN: 978-8187332961.

Bharati, S. V. (2006). Yogi in the Lab.

Bidelman, G. M., Price, C. N., Shen, D., Arnott, S. R., & Alain, C. (2019). Afferent-efferent connectivity between auditory brainstem and cortex accounts for poorer speech-in-noise comprehension in older adults. Hearing research, 382, 107795.

Bornot, J. M. S., Wong-Lin, K., Ahmad, A. L., & Prasad, G. (2018). Robust EEG/MEG based functional connectivity with the envelope of the imaginary coherence: sensor space analysis. Brain topography, 31(6), 895-916.

Bowyer, S. M. (2016). Coherence a measure of the brain networks: past and present. Neuropsychiatric Electrophysiology, 2(1), 1-12.

Braboszcz, C., Cahn, B. R., Levy, J., Fernandez, M., & Delorme, A. (2017). Increased gamma brainwave amplitude compared to control in three different meditation traditions. PloS one, 12(1), e0170647.

Bruña, R., Maestú, F., & Pereda, E. (2018). Phase locking value revisited: teaching new tricks to an old dog. Journal of neural engineering, 15(5), 056011.

Burle, B., Spieser, L., Roger, C., Casini, L., Hasbroucq, T., & Vidal, F. (2015). Spatial and temporal resolutions of EEG: Is it really black and white? A scalp current density view. International Journal of Psychophysiology, 97(3), 210-220.

Buzsaki, G. (2006). Rhythms of the Brain. Oxford university press.

Bærentsen, K. B. (2015). Patanjali and neuroscientific research on meditation. Frontiers in psychology, 6, 915.

Cahn, B. R., & Polich, J. (2006). Meditation states and traits: EEG, ERP, and neuroimagingstudies. Psychological bulletin, 132(2), 180.

Canolty, R. T., & Knight, R. T. (2010). The functional role of cross-frequency coupling. Trends in cognitive sciences, 14(11), 506-515.

Chen, W. L., Wagner, J., Heugel, N., Sugar, J., Lee, Y. W., Conant, L., ... & Whelan, H. T. (2020). Functional near-infrared spectroscopy and its clinical application in the field of neuroscience: advances and future directions. Frontiers in Neuroscience, 14, 724.

Cohen, M. X. (2015). Effects of time lag and frequency matching on phase-based connectivity. Journal of neuroscience methods, 250, 137-146.

Cohen, M. X. (2014). Analyzing neural time series data: theory and practice. MIT press.

Crosson, B., Ford, A., McGregor, K. M., Meinzer, M., Cheshkov, S., Li, X., ... & Briggs, R. W. (2010). Functional imaging and related techniques: an introduction for rehabilitation researchers. Journal of rehabilitation research and development, 47(2), vii. Easwaran, Eknath (2018). The Bhagavad Gita: (Classics of Indian Spirituality). Nilgiri Press. ISBN 978-1-58638-019-9.

Faes, L., Erla, S., & Nollo, G. (2012). Measuring connectivity in linear multivariate processes: definitions, interpretation, and practical analysis. Computational and mathematical methods in medicine, 2012.

Fujino, M., Ueda, Y., Mizuhara, H., Saiki, J., & Nomura, M. (2018). Open monitoring meditation reduces the involvement of brain regions related to memory function. Scientific reports, 8(1), 1-10.

Glover, G. H. (2011). Overview of functional magnetic resonance imaging. NeurosurgeryClinics,

22(2), 133-139.

Hauk, O., Stenroos, M., & Treder, M. (2019). Towards an objective evaluation of EEG/MEG source estimation methods: The Linear Tool Kit. BioRxiv, 672956.

Haumann, N. T., Parkkonen, L., Kliuchko, M., Vuust, P., & Brattico, E. (2016). Comparing the performance of popular MEG/EEG artifact correction methods in an evoked-response study. Computational Intelligence and Neuroscience, 2016.

Hata, M., Kazui, H., Tanaka, T., Ishii, R., Canuet, L., Pascual-Marqui, R. D., ... & Takeda, M. (2016). Functional connectivity assessed by resting state EEG correlates with cognitive decline of Alzheimer's disease–An eLORETA study. Clinical Neurophysiology, 127(2), 1269-1278.

Hülsemann, M. J., Naumann, E., & Rasch, B. (2019). Quantification of phase-amplitude coupling in neuronal oscillations: comparison of phase-locking value, mean vector length, modulation index, andgeneralized-linear-modeling-cross-frequency-coupling. Frontiers in neuroscience, 13, 573.

Huotari, N., Raitamaa, L., Helakari, H., Kananen, J., Raatikainen, V., Rasila, A., ... & Korhonen, V. O. (2019). Sampling rate effects on resting state fMRI metrics. Frontiers in Neuroscience, 13, 279.

Involving, R. I. M. E. (2007). Safety Guidelines for Conducting Magnetic Resonance Imaging (MRI) Experiments Involving Human Subjects.

Ives-Deliperi, V. L., Howells, F., Stein, D. J., Meintjes, E. M., & Horn, N. (2013). The effects of mindfulness-based cognitive therapy in patients with bipolar disorder: a controlled functional MRI investigation. Journal of affective disorders, 150(3), 1152-1157.

Izzetoglu, M., Shewokis, P. A., Tsai, K., Dantoin, P., Sparango, K., & Min, K. (2020). Short-Term Effects of Meditation on Sustained Attention as Measured by fNIRS. Brain Sciences, 10(9), 608.

Jaiswal, A., Nenonen, J., Stenroos, M., Gramfort, A., Dalal, S. S., Westner, B. U., ... & Parkkonen, L. (2020). Comparison of beamformer implementations for MEG sourcelocalization. NeuroImage, 216, 116797.

Jones, P. (2019). Mindfulness training: Can it create superheroes?.Frontiers in Psychology, 10, 613.

Kasamatsu, A., & Hirai, T. (1966). An electroencephalographic study on the Zen meditation(Zazen).

Psychiatry and Clinical Neurosciences, 20(4), 315-336.

Kaur, C., & Singh, P. (2015). EEG derived neuronal dynamics during meditation: progress and challenges. Advances in preventive medicine, 2015.

Kelly, E. F., Kelly, E. W., Crabtree, A., Gauld, A., &Grosso, M. (2007). Irreducible mind: Toward a psychology for the 21st century. Rowman& Littlefield.

Keil, B., Blau, J. N., Biber, S., Hoecht, P., Tountcheva, V., Setsompop, K., ... & Wald, L. L. (2013). A 64-channel 3T array coil for accelerated brain MRI. Magnetic resonance in medicine, 70(1), 248-258.

Kim, Y. J., Savukov, I., & Newman, S. (2019). Magnetocardiography with a 16-channel fiber-coupled single-cell Rb optically pumped magnetometer. Applied Physics Letters, 114(14), 143702.

Kovach, C. K. (2017). A biased look at phase locking: Brief critical review and proposedremedy. IEEE Transactions on signal processing, 65(17), 4468-4480.

Kristeller, J. L. (2007). Mindfulness meditation.

Lee, D. J., Kulubya, E., Goldin, P., Goodarzi, A., &Girgis, F. (2018). Review of the neural oscillations underlying meditation. Frontiers in neuroscience, 12, 178.

Lansky, E. P., & Louis, E. K. S. (2006). Transcendental meditation: a double-edged sword in epilepsy?. Epilepsy & Behavior, 9(3), 394-400.

Lau, T. M., Gwin, J. T., McDowell, K. G., & Ferris, D. P. (2012). Weighted phase lag index stability as an artifact resistant measure to detect cognitive EEG activity during locomotion. Journal of neuroengineering and rehabilitation, 9(1), 1-9.

Llana, T., Fernandez-Baizan, C., Mendez-Lopez, M., Fidalgo, C., & Mendez, M. (2022). Functional near-infrared spectroscopy in the neuropsychological assessment of spatial memory: A systematic review. Acta Psychologica, 224, 103525.

Liao, X., Vasilakos, A. V., & He, Y. (2017). Small-world human brain networks: perspectives and challenges. Neuroscience & Biobehavioral Reviews, 77, 286-300.

Li, G., Wu, J., Xia, Y., He, Q., & Jin, H. (2020). Review of semi-dry electrodes for EEG recording. Journal of Neural Engineering.

Light, G. A., Williams, L. E., Minow, F., Sprock, J., Rissling, A., Sharp, R., ... & Braff, D. L. (2010). Electroencephalography (EEG) and event-related potentials (ERPs) with human participants. Current protocols in neuroscience, 52(1), 6-25.

Linne, M. L., & Acimovic, D. J. (2021). SENSITIVITY ANALYSIS IN COMPUTATIONAL NEUROSCIENCE. Science and engineering

MacLean, K., Ferrer, E., Aichele, S., Bridwell, D., Zanesco, A., Jacobs, T., King, B., Rosenberg, E., Sahdra, B., Shaver, P., et al. (2010). Intensive meditation training improves perceptual discrimination and sustained attention. Psychological Science, 21(6):829.

Marciniak, R., Sheardova, K., Čermáková, P., Hudeček, D., Šumec, R., & Hort, J. (2014). Effect of meditation on cognitive functions in context of aging and neurodegenerative diseases. Frontiers in behavioral neuroscience, 8, 17.

Markan, CM., Gupta, P (2015) Unraveling The Mystery of The Observer Through Sampling Theorem, Towards Science of Consciousness TSC 2015, Helsinki, Finland.

Matsuda, T., & Komaki, F. (2017). Time series decomposition into oscillation components and phase estimation. Neural computation, 29(2), 332-367.

Markan, CM., Gupta, P (2015) Unraveling The Mystery of The Observer Through Sampling Theorem, Towards Science of Consciousness TSC 2015, Helsinki, Finland.

Marzetti, L., Basti, A., Chella, F., D'Andrea, A., Syrjälä, J., & Pizzella, V. (2019). Brain functional connectivity through phase coupling of neuronal oscillations: a perspective from magnetoencephalography. Frontiers in neuroscience, 13, 964.

Marzetti, L., Della Penna, S., Snyder, A. Z., Pizzella, V., Nolte, G., De Pasquale, F., ... & Corbetta, M. (2013). Frequency specific interactions of MEG resting state activity within and across brain networks as revealed by the multivariate interaction measure. Neuroimage, 79, 172-183.

Matko, K., &Sedlmeier, P. (2019). What is Meditation? Proposing an Empirically-Derived Classification System. Frontiers in psychology, 10, 2276.

Mohseni, H. R., Woolrich, M. W., Kringelbach, M. L., Luckhoo, H., Smith, P. P., & Aziz, T. Z. (2012). Fusion of magnetometer and gradiometer sensors of MEG in the presence of multiplicative error. IEEE transactions on biomedical engineering, 59(7), 1951-1961.

Montoya-Martínez, J., Vanthornhout, J., Bertrand, A., & Francart, T. (2021). Effect of number and placement of EEG electrodes on measurement of neural tracking of speech. Plos one, 16(2), e0246769.

Nakata, H., Sakamoto, K., & Kakigi, R. (2014). Meditation reduces pain-related neural activity in the anterior cingulate cortex, insula, secondary somatosensory cortex, and thalamus. Frontiers in psychology, 5, 1489.

Nolte, G., Ziehe, A., Nikulin, V. V., Schlögl, A., Krämer, N., Brismar, T., & Müller, K. R. (2008). Robustly estimating the flow direction of information in complex physical systems. Physical review letters, 100(23), 234101.

Nolte, G., Ziehe, A., Krämer, N., Popescu, F., & Müller, K. R. (2010, February). Comparison of granger causality and phase slope index. In Causality: objectives and assessment (pp. 267-276). PMLR.

Pagnoni, G., Cekic, M., &Guo, Y. (2008). "Thinking about not-thinking": neural correlates of conceptual processing during Zen meditation. PLoS One, 3(9).

Pascual-Marqui, R. D., Faber, P., Kinoshita, T., Kochi, K., Milz, P., Nishida, K., & Yoshimura, M. (2018). A comparison of bivariate frequency domain measures of electrophysiological connectivity. bioRxiv, 459503.

Pascual-Marqui, R. D. (2007). Instantaneous and lagged measurements of linear and nonlinear dependence between groups of multivariate time series: frequency decomposition. arXiv preprint arXiv:0711.1455.

Pascual-Marqui, R. D. (2002). Standardized low-resolution brain electromagnetic tomography (sLORETA): technical details. Methods Find ExpClinPharmacol, 24(Suppl D), 5-12.

Piron, H. (2001). The meditation depth index (MEDI) and the meditation depth questionnaire (MEDEQ). Journal for Meditation and Meditation Research, 1(1), 69-92.

Quaresima, V., & Ferrari, M. (2019). Functional near-infrared spectroscopy (fNIRS) for assessing cerebral cortex function during human behavior in natural/social situations: a concise review. Organizational Research Methods, 22(1), 46-68.

Reddy, J., & Roy, S. (2018). Commentary: Patanjali and neuroscientific research on meditation.

Frontiers in psychology, 9, 248.

ROSENBLUM, M., TASS, P., Kurths, J., VOLKMANN, J., SCHNITZLER, A., & FREUND, H. J. (2000). Detection of phase locking from noisy data: application to magnetoencephalography.In Chaos In Brain? (pp. 34-51).

Roth, R. (1987). Transcendental meditation.

Runge, J., Heitzig, J., Petoukhov, V., & Kurths, J. (2012). Escaping the curse of dimensionality in estimating multivariate transfer entropy. Physical review letters, 108(25), 258701.

Sahdra, B., MacLean, K., Ferrer, E., Shaver, P., Rosenberg, E., Jacobs, T., Zanesco, A., King, B., Aichele, S., Bridwell, D., et al. (2011). Enhanced response inhibition during intensive meditation training predicts improvements in self-reported adaptive socioemotional functioning. Emotion, 11(2):299.

Samuelsson, J. G., Peled, N., Mamashli, F., Ahveninen, J., & Hämäläinen, M. S. (2021). Spatial fidelity of MEG/EEG source estimates: A general evaluation approach. Neuroimage, 224, 117430.

Satsangi P.S., Sahni V. (2015), "Power Law of Meditational Consciousness", Concurrent Session on Meditation, Toward a Science of Consciousness (TSC 2015), Helsinki, Finland, June 2015, Abstract Book, pp. 340.

Satsangi, P. S. (2013) Vision Talk, Towards Science of Consciousness 2013, DEI, Agra (https://www.dayalbagh.org.in/specialTalks/visiontalkTSC2013.htm).

Satsangi, P. S. (2011). Cosmology of Consciousness: Towards Quantum-theoretic Systems Modelling; Spirit-Mind-Brain.

Sedlmeier, P., &Srinivas, K. (2016). How Do Theories of Cognition and Consciousness in Ancient Indian Thought Systems Relate to Current Western Theorizing and Research?. Frontiers in psychology, 7, 343.

Song, J., Davey, C., Poulsen, C., Luu, P., Turovets, S., Anderson, E., ... & Tucker, D. (2015). EEG source localization: sensor density and head surface coverage. Journal of neuroscience methods, 256, 9-21.

Singh, S. P. (2014). Magnetoencephalography: basic principles. Annals of Indian Academy of

Neurology, 17(Suppl 1), S107.

Slagter, H., Lutz, A., Greischar, L., Francis, A., Nieuwenhuis, S., Davis, J., and Davidson, R. (2007). Mental training affects distribution of limited brain resources. PLoS Biol, 5(6):e138.

Smits, K. (2020). Studies on the spatial resolution in magnetoencephalography.

Solomon Jr, O. M. (1991). PSD computations using Welch's method. [Power Spectral Density (PSD)] (No. SAND-91-1533). Sandia National Labs., Albuquerque, NM (United States).

Srivastava, D. P., Sahni, V., & Satsangi, P. S. (2017). From n-qubit multi-particle quantum teleportation modelling to n-qudit contextuality based quantum teleportation and beyond. International Journal of General Systems, 46(4), 414-435.

Stam, C. J., Nolte, G., & Daffertshofer, A. (2007). Phase lag index: assessment of functional connectivity from multi-channel EEG and MEG with diminished bias from common sources. Human brain mapping, 28(11), 1178-1193.

Stapleton, P., Dispenza, J., McGill, S., Sabot, D., Peach, M., & Raynor, D. (2020). Large effects of brief meditation intervention on EEG spectra in meditation novices. IBRO reports, 9, 290-301.

Tadel, F., Baillet, S., Mosher, J. C., Pantazis, D., & Leahy, R. M. (2011). Brainstorm: a user-friendly application for MEG/EEG analysis. Computational intelligence and neuroscience, 2011.

Tang, Y. Y. (2017). Traits and states in mindfulness meditation. The neuroscience of mindfulness meditation, 29-34.

Tomasino, B., Chiesa, A., &Fabbro, F. (2014). Disentangling the neural mechanisms involved in Hinduism-and Buddhism-related meditations. Brain and Cognition, 90, 32-40.

Tort, A. B., Komorowski, R., Eichenbaum, H., & Kopell, N. (2010). Measuring phase-amplitude coupling between neuronal oscillations of different frequencies. Journal of neurophysiology, 104(2), 1195-1210.

Travis, F., Haaga, D. A., Hagelin, J., Tanner, M., Nidich, S., Gaylord-King, C., ... & Schneider, R. H. (2009). Effects of Transcendental Meditation practice on brain functioning and stress reactivity incollege students. International Journal of Psychophysiology, 71(2), 170-176.

Tsow, F., Kumar, A., Hosseini, S. H., & Bowden, A. (2021). A low-cost, wearable, do-it-yourself functional near-infrared spectroscopy (DIY-fNIRS) headband. HardwareX, 10, e00204.

Velmurugan, J., Sinha, S., & Satishchandra, P. (2014). Magnetoencephalography recording and analysis. Annals of Indian Academy of Neurology, 17(Suppl 1), S113.

Vicente, R., Wibral, M., Lindner, M., & Pipa, G. (2011). Transfer entropy—a model-free measure of effective connectivity for the neurosciences. Journal of computational neuroscience, 30(1), 45-67.

Volk, D., Dubinin, I., Myasnikova, A., Gutkin, B., & Nikulin, V. V. (2018). Generalized cross-frequency decomposition: a method for the extraction of neuronal components coupled at different frequencies. Frontiers in neuroinformatics, 12, 72.

Walsh, R., & Shapiro, S. L. (2006). The meeting of meditative disciplines and Western psychology: a mutually enriching dialogue. American psychologist, 61(3), 227.

Zotev, V. S., Matlashov, A. N., Volegov, P. L., Savukov, I. M., Espy, M. A., Mosher, J. C., ... & Kraus Jr, R. H. (2008). Microtesla MRI of the human brain combined with MEG. Journal of Magnetic Resonance, 194(1), 115-120.

Appendix: Connectivity measure

Connectivity measure	Advantages	Disadvantages
Coherence (COH)– measures phase coupling between signals at a given frequency. It quantifies the frequency and amplitude of the synchronicity of neural patterns of oscillating brain activities (Marzetti L et al., 2019; Bowyer S M, 2016).	Coherence has been widely used to differentiate patients with disorder brains, say epilepsy, Alzheimer's, etc. (BowyerS M, 2016).	This method is sensitive for studying rapid temporal changes in synchronized activity (Bowyer S M, 2016). Coherence measure in source space is affected by source leakage i.e., artificial zero-lag correlations & volume conduction (Marzetti L et al., 2019).
Imaginary Coherence (iCOH)– measures the complex value of coherence projected onto the imaginary axis (Bastos A M & Schoffelen J M, 2016).	iCOH is an effective technique as it eliminates the effect of volume conduction in sensor and source space (Bornot J M S et al., 2018).	It explicitly eliminates the effect due to true interactions. So, this method is not preferred when true interactions exist (Bornot J M S et al., 2018).
Phase locking value (PLV)– assumes that if two brain regions are connected i.e., the instantaneous phase difference between signals from the two brain regions will be constant. The phase of signals gets extracted from the Hilbert transform or wavelet transforms (Bruña R et al., 2018).	It determines the interaction of two regions in a narrow time band. So, suitable for studying cognitive tasks with shorter events (Bruña R et al., 2018; Bowyer S M, 2016).	Computation of analytic phase involves normalization of signal, and its envelope may induce the effect of spectral component outside the band of interest (filtered band). This may mislead the results (Kovach C K, 2017; Bowyer S M, 2016; Bruña R et al., 2018).
Imaginary-phase locking value (iPLV) - measures the complex values of PLV projected onto the imaginary axis (Marzetti L et al., 2019).	iPLV measure is insensitive to zero lag effects and thus eliminates the effect of volume conduction and source leakage (Bruña R et al., 2018).	It eliminates the effect due to the constant phase difference between the signals (Bruña R et al., 2018).
Phase lag index (PLI) – measures the asymmetry of the distributions of the instantaneous phase difference between signals. Asymmetry of the phase distribution means phase difference will be within the interval. It measures the consistent non-zero phase lag between the signals (Stam C J et al., 2007).	Non-zero phase lag between signals (volume induction) can be measured using PLI, which cannot be by iPLV. It measures both the phase synchronizations and the imaginary part of phase synchronizations. So, widely used to study disordered brain say Alzheimer's, epilepsy, etc. (Stam C J et al., 2007)	The PLV value will drop to zero when the phase difference between the signals are around zero or Π, but this may be due to a mismatch in the frequency of oscillations. In such cases, results may lead to misinterpretations (Cohen M X, 2015).
Weighted phase lag index (wPLI)– an extended measure of PLI, introduces a phase-difference weighted normalization term (Cohen M X, 2015).	wPLI method adapted in neurotechnological studies. These studies include brain-computer interface devices, machine learning (Lau T M et al., 2012).	wPLI estimates the errors of connectivity when there are minor violations of stationary frequency (frequency mismatch). So, this method is not suitable to study time course of changes in connectivity (Cohen M X, 2015).

Lagged coherence (LC)– measures the connectivity between two complex-valued signals.	Lagged coherence is invariant to volume induction and low spatial resolution (especially for EEG). It outperforms wPLI, PLI, and iCOH (Pascual- Marqui, R. D et al., 2018; Hata, M et al., 2016).	As LC is insensitive to volume conduction, it may ignore true interactions due to small-time lags or frequency mismatch (Cohen M X, 2015).
Multivariate interaction measure (MIM) – measures the true interaction between multivariate time series of signals based on complex coherence (Marzetti, L et al., 2013).	MIM sustain a measure of phase-shifted interaction between multivariate time series with long periods (Say fMRI; minutes). (Faes, L et al., 2012; Marzetti, L et al., 2013).	Model order number selection is difficult for the original data set as the true order is not known. Low- value results in the inability to describe the essential information of MV time series high value overfits the effects implants noise (Faes, L et al., 2012).
Multivariate lagged coherence (MLC)– measures the phase synchronization between several brain locations with distributed cortical activity or multivariate time series (Pascual-Marqui R D, 2007).	The main advantage of this method over univariate measures is the investigation of distributed cortical networks and test joint dependence of several locations (Pascual-Marqui R D, 2007).	MVC is insensitive to instantaneous coupling. This method is not suitable for measuring non-linear coupling (Basti A et al., 2020).
n:m phase-locking value (PLVn:m)– measures the synchronization of two periodic non-identical oscillators with frequency locking condition (nf1=mf2) i.e., phase synchronization is possible when natural frequencies are in a rational relation (Rosenblum, M et al., 2000).	This measure investigates frequency phase-locking of neuronal spikes within working memory tasks and many cognitive processes (Canolty, R. T et al., 2010).	This measure is sensitive to volume conduction. This measure ignores the contributions of true interactions within networks of source patterns (Volk, D et al., 2018).
Bicoherence (Bic)– is a tensor defined for three different signals that measure the nonlinear interaction between three signals oscillating at three different frequencies (Bartz, S et al., 2020).	The bicoherence approach does not rely on repeated bandwidth-filtering, estimates at high-frequency resolution and low computational cost (Bartz, S et al., 2020).	This measure is sensitive to volume conduction over the sensor space (Bartz, S et al., 2020). The measure is affected by artificial zero-lag correlations (Marzetti L et al., 2019).
Antisymmetric part of bicoherence (aBic)– this measure is analog to iCOH and consists of both imaginary part and arbitrary phase part (Bartz, S et al., 2020).	aBic measure is robust to volume conduction as it vanishes when the sources are independent or interactions between sources are pairwise (Bartz, S et al., 2020).	This measure is not yet applicable to estimate coupling between triple voxels (source localization) as it's too costly (Bartz, S et al., 2020).

Phase Locking Value (PLV) – measure phase-amplitude coupling in terms of a constant phase difference between time series. PLV measure includes extraction of the phase of low frequency and amplitude of high frequency. Then again phase is extracted from amplitude time series of high frequency to calculate phase lag (Hülsemann, M. J et al., 2019).	Many task-based studies (say learning) have shown frequency-based coupling between different brain regions (Canolty, R. T et al., 2010). PLV is least affected by the sampling rate and noise.	The extracted low-frequency phase information should only be from a narrow band. PLV is affected by data length (Hülsemann, M. J et al., 2019).
Mean vector length (MVL)- measures the phase of low-frequency signal and amplitude of the high-frequency signal. Then the complex value is mapped to a polar plane to extract the magnitude M high, especially at a specific phase or at a narrow range. Then the average of all the resultant vectors gives mean vector length (Hülsemann, M. J et al., 2019).	This method is suitable when phase angles follow a uniform distribution. One should ensure no outliers exist in the absolute values of the amplitude-frequency signal as this method is independent of outliers (Tort, A. B et al., 2010).	The measure remains invariant for absolute amplitude values of the high-frequency signal. The non-distributed phase angles may affect the MVL value while averaging. So, further statistical testing would be necessary. MLV is sensitive to modulations in coupling strength and width (Hülsemann, M. J et al., 2019).
Modulation index (MI)- measures phase-amplitude coupling as a ratio of Kullback-Leibler distance and logN i.e., uniform distribution N phase bins between -1800 to 1800 (generally N=18 is preferred). Kullback-Leibler distance is a measure of disparity between two distributions (Hülsemann, M. J et al., 2019).	MI is a robust measure of phase-amplitude coupling for noisy, short data epochs (this measure is least affected by data length). MI is least sensitive to modulations (Hülsemann, M. J et al., 2019).	MI measures are sensitive to the number of bins, amount of data squeezed into bins. This affects the degree of freedom (Hülsemann, M. J et al., 2019).
Phase slope index (PSI)- computes the complex-valued coherence along with the direction of change in phase between different frequencies, it computes phase difference in each frequency bin weighted with coherence. The sign of PSI represents which signal is temporally leading the other one (Bastos, A. M et al., 2016).	This method best suits when the information flow is unidirectional without noise contamination (Nolte, G et al., 2008).	This measure is sensitive if information flow is bidirectional or associated with directed noise. The measure is sensitive to artifactual detection and artificial zero-lag correlations (Nolte, G et al., 2008).
Phase transfer entropy (pTE)– estimated using the time series of instantaneous phases of pairwise signals (Bidelman G M Price et al., 2019).	pTE is asymmetric so can estimate bi-directional causal relation between signals (Bidelman G M Price et al., 2019).	If two systems exhibit a deterministic map i.e., complete synchronization, then causal relation won't exist. So, pTE cannot be used (Vicente, R et al., 2011).

Granger causality (GC) – measures the total interdependence of signals both in time and frequency domains using cross-spectral density estimates. Directed interactions are measured using auto-regressive models (Bastos A M & Schoffelen J M, 2016).	GC quantifies bi-directional interactions and provides two estimates of directed connectivity for a given signal pair (Bastos A M & Schoffelen J M, 2016).	GC is sensitive to mixture of independent noise sources and due to which the results can be misleading (Nolte, G et al., 2008; Nolte, G et al., 2010).
Multivariate phase slope index (MPSI)- measures the interaction between three signals (minimum). An averaging process is carried out based on the calculations of PSI between all possible combinations of transformed signals (Basti A et al., 2018).	The measure is insensitive to linear static transformations of data i.e., rotation of data spaces (Basti, A et al., 2018). MPSI solely detects the directionality of phase lagged coherence (Marzetti L et al., 2019).	MPSI is sensitive to high-dimensional spaces because it involves infinite vectors (Runge, J et al., 2012).

Table: Represents various connectivity measures with their definition, potential advantages include benefits, preferred experimental settings, and caveats include sensitivity along with a description of possible misinterpretations.